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A Citizen Science Approach to the Characterisation and Modelling of Urban Pluvial Flooding

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ABSTRACT: Urban pluvial flooding (UPF), a growing challenge across cities worldwide that is expected to worsen due to climate change and urbanisation, requires comprehensive response strategies. However, the characterisation and simulation of UPF is more complex than traditional catchment hydrological modelling because UPF is driven by a complex set of interconnected factors and modelling constraints. Different integrated approaches have attempted to address UPF by coupling humans and environmental systems and reflecting on the possible outcomes from the interactions among varied disciplines. Nonetheless, it is argued that current integrated approaches are insufficient. To further improve the characterisation and modelling of UPF, this study advances a citizen science approach that integrates local knowledge with the understanding and interpretation of UPF. The proposed framework provides an avenue to couple quantitative and qualitative community-based observations with traditional sources of hydro-information. This approach allows researchers and practitioners to fill spatial and temporal data gaps in urban catchments and hydrologic/hydrodynamic models, thus yielding a more accurate characterisation of local catchment response and improving rainfall-runoff modelling of UPF. The results of applying this framework indicate how community-based practices provide a bi-directional learning context between experts and residents, which can contribute to resilience building by providing UPF knowledge necessary for risk reduction and response to extreme flooding events.

KEYWORDS: Urban pluvial flooding, citizen science, flood modelling, participatory mapping, catchment characterisation, Tennessee, USA

INTRODUCTION

Urban pluvial flooding (UPF) refers to inundation caused by intense and localised rainfall, resulting from the depth of overland flow of water runoff generated from pervious and impervious urban surfaces before such runoff enters the drainage system or else when water runoff rates locally exceed the capacity of the stormwater drainage system (Falconer et al., 2009; Ochoa-Rodríguez et al., 2013). Notwithstanding its localised nature, UPF can cause property damage and loss of life, often inordinately affecting lower income populations, and it is expected to worsen given increasing instances of extreme rainfall and urbanisation worldwide (Rözer et al., 2021; Trenberth, 2011; Fowler et al., 2021).

Despite its significant impact and importance, UPF has received little attention compared to other types of flooding, such as fluvial or coastal flooding (Arosio et al., 2020; Huang et al., 2020; Bates et al., 2021; Rosenzweig et al., 2021). A first reason for this is that UPF is often framed as an already solved technical problem (Rosenzweig et al., 2018) without considering that its physical and technical dimensions usually interact with varied urban socio-environmental challenges. Moreover, there is an underlying assumption that UPF represents only a nuisance-type flooding, corresponding to smaller, chronic urban inundation events with minimal impact (Moftakhari et al., 2017). Additionally, there are documented gaps in the hydrological models used to predict UPF in practice (Revilla-Romero et al., 2015), which are compounded by the scarcity of hydro-meteorological data in urban catchments at the scales of interest (small, neighbourhood-scale drainage basins, including headwater locations close to the water divides).

Technically, urban catchments are spatially and temporally complex and variable, making UPF events hard to characterise given that they are infrequent, spatially localised, short-lived, and common to locations without any type of formal monitoring (Downtown, 2015; Marjerison et al., 2016; Fahy et al., 2019). To assess the risk of UPF and then design solutions to tackle its effects, urban drainage experts use numerical rainfall-runoff modelling tools to simulate the water accumulation and flow over urban catchments. These hydrologic-hydraulic models vary in complexity, depending mainly on the way surface water flows are represented, the completeness of the flow equations, and the complexity with which sewer-surface interactions are depicted (if included at all). No matter their level of complexity, all models that attempt to simulate the complicated physical nature of UPF have limitations. Among these is the fact that they have parameters that need to be calibrated against data that are often missing (Thorndahl et al., 2008). This requirement definitely applies for conceptual models – and most models are either entirely conceptual at the catchment scale (i.e. lumped) or are semi-distributed, with conceptual components applied across sub-areas within the catchment (Beven, 2011; Bulti et al., 2020), but calibration is also required for physically based models, as discussed below.

As compared to traditional hydrological models, current urban flood models attempt to simulate and reflect the physical processes at greater details of spatio-temporal resolution (Qi et al., 2021). Two-dimensional (2D) or 1D-2D models are usually used for this purpose as they can comprehensively represent flow hydrodynamics and small-scale topographic features. These physically based models require vast amounts of data to represent the actual hydrological processes, e.g. a Digital Elevation Model (DEM), a drainage network layout, and a range of characteristics (such as slope, roughness, etc) for the various landscape elements, including roads, slopes, buildings, and waterways. The availability of high-resolution topographic data is crucial for 2D flood modelling, as it allows for accurate delineation of urban features such as buildings and streets. This highlights the importance of high-quality, high-resolution data when modelling urban flooding (Wang et al., 2018). Attempting to apply such detailed models without adequate data can cause major issues in UPF modelling, as it amplifies the uncertainties in the output (Liu et al., 2020).

In theory, physically based models purport to represent the actual hydrological and hydraulic processes taking place so that they would not need any calibration parameters. In practice though, the mismatch between the process scale and the coarser resolution at which flood information can be actually collected means that these models require calibration based on concurrent rainfall and runoff records (Bellos et al., 2020). Despite the recognised necessity of calibrating hydrologic-hydrodynamic urban drainage models to reduce their uncertainties, this is rarely performed due to the aforementioned data gaps (Tscheikner-Gratl et al., 2016). In addition, conventional sensors designed for sewer pipes or well-defined channels are not suited to open urban environments such as streets, grassed slopes, driveways, and/or areas at risk of vandalism (Moy de Vitry, 2019). Albeit constrained by time and resources, a way to address these challenges is to perform field measurements of flooding discharge at multiple locations, and over sufficiently long periods, to model processes occurring when the catchment is flooding (Seibert and Beven, 2009; Tada and Beven, 2012).

Even though discharge measurements at the outlet of an urban catchment (or outlets of a few nested subcatchments) are available in some rare research cases, bearing their own uncertainties (Di Baldassarre et al., 2012), there is a much broader, crucial issue at play here: such outflow hydrographs integrate the hydrological response over time and space, so that only the flood runoff at the outlet is known; what has actually occurred upstream, over each slope, street, or smaller channel within the catchment cannot be recovered from this type of data. In this way, a model calibrated and validated with discharge data at the basin's outlet may not represent runoff depths and velocities correctly at specific locations inside the catchment, even if the model can 'correctly' reproduce discharge at the gauged location. From applying improved technologies and sensors to obtaining more detailed data from residents, different alternatives have been used to address some of these gaps in recent years. This research focuses on the latter, by engaging residents to obtain detailed data and then integrating that information at distributed locations within the catchment.

Furthermore, more recent attempts at comprehending cities as integrated socio-environmental systems have also called for a paradigm shift towards more interdisciplinary, people-oriented frameworks, coupling humans with environmental systems (Joseph, 2013; Fainstein, 2015). This is apparent in new approaches such as citizen science (Bonney et al., 2009; See et al., 2016; Zheng et al., 2018; Kobori et al., 2019; Wolff, 2021), which emphasise the relevance of the socio-economic and political contexts of environmental hazards (Smith, 2013). To ameliorate issues of low quality and/or missing data, and to better understand and model UPF, many scholars engage citizen science to take advantage of people's knowledge to fill data gaps, arguing that residents can provide inputs for developing hydrological models (Voinov et al., 2016). In such citizen science studies, citizens are involved in scientific processes of research design and data collection (Pánek et al., 2017; Starkey et al., 2017; see Golparvar and Wang, 2020; Goodrich et al., 2020; Puttinaovarat and Horkaew, 2020; Forrest et al., 2021). Studies using citizen science in flood modelling demonstrate its value in providing data for informing, calibrating, and validating flood models, as well as determining flooding extents, particularly where data are scarce (Blumberg et al., 2015; Liu et al., 2016; Le Coz et al., 2016; Smith and Rodriguez, 2017; Paul et al., 2018; Assumpção et al., 2018; Tian et al., 2019). In many studies though, citizens act mainly as sensors, only providing data about UPF that are subsequently analysed by the researchers (Wolf, 2021). By contrast, we propose that it is necessary to create opportunities for participants to express their own perceptions and interpretations of the flooding.

Citizen science approaches for a more integrated understanding of UPF also have some shortcomings. For example, the data collected may be limited in terms of the sample size or the number of years over which they are available (Townsend and Walsh, 1998). Depending on the technique or technology, it can also be costly (Houghton-Carr, 2014). A common criticism is that many citizen science studies are conceived as one-way processes, where information flows from citizens to experts – with people typically used only to generate data (Conrad and Hilchey, 2011; Couvet and Prevot, 2015; Wolff, 2021; Wolff et al., 2021). Besides, we argue that in flood modelling, only very basic data are usually collected, and these data cannot begin to adequately address the challenges of complex models. Moreover, most applied citizen science modelling approaches have been used in the model application phase rather than during model development. Specifically, we propose that more can be done to utilise stakeholders' knowledge across all phases of an urban flood model (data collection, development, and improvement) – especially in those areas with little or no formal data available to build a hydrodynamic model in the first place (Gebremedhin et al., 2020). Moreover, because of primary concerns with the quality and accuracy of citizen data, citizen science approaches are frequently met with skepticism or mistrust from scientists, and strong resistance from policymakers (Dickinson et al., 2012). Other issues discussed in the literature include the potential range of citizens involved and their motivations to contribute information (Flanagin and Metzger, 2008), the sources of information (Kosmala et al., 2016; Voinov et al., 2016), the level of participation (Crall et al., 2011; Shirk et al., 2012; Veiga et al., 2017), variations in sampling and data collection methodologies (Anhalt-Depies et al., 2019), inadequate sample size (Stevenson et al., 2021), and the application of collected data (Hunter et al., 2013); all of these can vary greatly, leading to a broad range of data quality challenges (accuracy, temporality, etc) when applying citizen science approaches (Lewandowski and Specht, 2015; Balázs et al., 2021).

Based on the above and on a recent review by Azizi et al. (2022), we identify the following general issues with respect to integrated, community-based approaches to modelling UPF: (i) limited availability of hydro-meteorological data and information about catchment characteristics at a level of detail that is adequate to capture the complex nature of urban settings and address the requirements of high-resolution, hydrologic-hydrodynamic models; (ii) divergence between the different disciplines involved, reflected in the lack of transdisciplinary, comprehensive methodologies that can simultaneously address the different dimensions of UPF; (iii) lack of bidirectional approaches for citizen participation in UPF research that go beyond data collection, involving earlier collaboration between researchers and residents that starts in the model development phase; and (iv) need for context-based approaches that account for resident's realities and perceptions regarding UPF issues.

Out of these four general research gaps, our research attempts to address points (i) and (iii). We apply a citizen science approach to better understand, characterise, and model the complex, integrated UPF process. Through this research methodology, we provide an avenue to advance and consolidate the integrated understanding of UPF risks, vulnerabilities, and participatory modelling by exploring ways in which residents can be involved throughout the cycle of urban flood risk assessment, data collection, and model development. Such an approach engages researchers and residents in a deep process of mutual learning, co-analysis, and data sharing in order to better understand and tackle UPF as a socio-environmental system.

The research methodology is applied in a US community that experienced a recent extreme flood; we reached out to its residents following this event. The data gathered through the participation of engaged residents were compared to the initial results from an advanced hydrodynamic model in order to further improve and validate the model. We posit that allowing for more community input results in more diverse data, more robust models, and better understanding and characterisation of UPF modelling necessary to enhance risk management.

RESEARCH FRAMEWORK

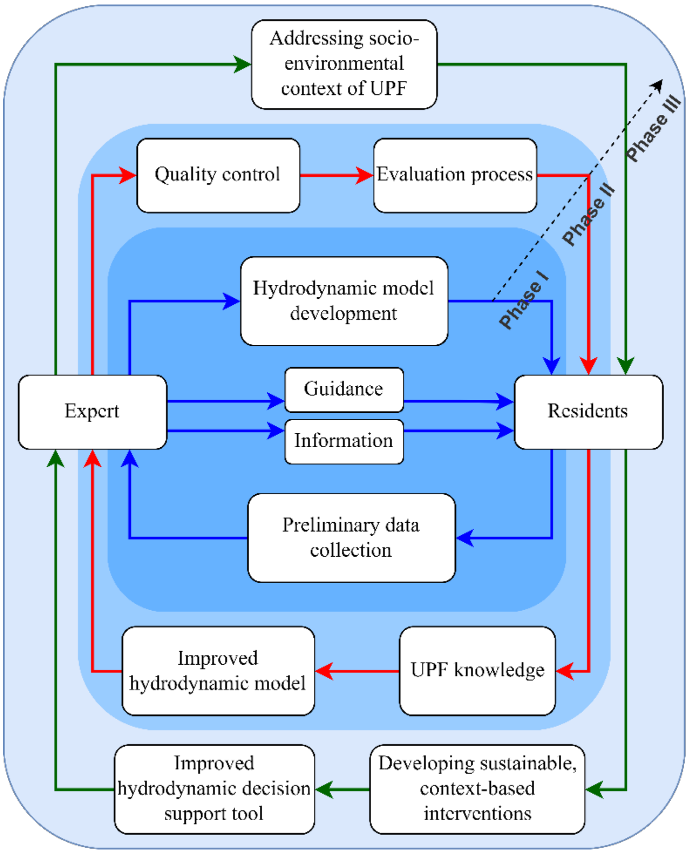
The research process comprises a participatory modelling method that integrates a hydrologic-hydrodynamic model with community-based data collection to achieve two main objectives: (i) to address data gaps in the hydrological models used to predict flooding in practice, including both data not directly related to any specific event (e.g. the layout of the existing drainage system) as well as data needed to reconstruct a past flooding episode across a catchment (if one has occurred) – both types of data are needed to improve and validate a hydrodynamic model; (ii) to engage local residents in defining the problem, collecting data, processing and analysing it, and modelling within a more profound, reciprocal process of learning, with the shared aim of improving the characterisation, modelling, and management of UPF, as well as enhancing residents' understanding of their own flooding risks. These objectives contribute to building resilience within the study area by providing the necessary UPF knowledge relevant for disaster risk reduction and response strategies. The combined quantitative and qualitative analyses (such as those of flooding risk and its perception, as well as vulnerability assessments) not only help improve the model, but also give context and provide opportunities for mutual learning between the researchers and residents in the process of developing a UPF model. This participatory framework for UPF modelling builds on residents' knowledge to improve 1D-2D urban flood models in three-layered iterative phases.

Phase I: Identifying UPF risk and priority areas

Traditionally, preliminary UPF risk and catchment analyses are done at the large scale of urban catchments (e.g. entire cities or large parts of them). These analyses try to identify areas that would be potentially endangered by a given extreme rainfall scenario, developing flood inundation maps and related hydraulic outputs (e.g. maximum water depths corresponding to different design rainfall hyetographs) through 1D-2D hydraulic modelling. This approach uses available information like LIDAR, DEM data, climate data (such as local depth-duration-frequency values for precipitation), existing stormwater infrastructure data, and official land-use maps. This type of analysis allows for preliminary identification of areas within the city that could be prone to urban flooding. We followed this approach to identify preliminary focus areas for our study.

At the end of Phase I of the research, we established an initial engagement (blue arrows, Figure 1) with residents who live close to the identified vulnerable locations by distributing online surveys, and we provided guidance on collecting required data for Phase II.

Figure 1. The participatory UPF modelling methodology.



Note: The dashed arrow depicts the subsequent research phases, with each layer or phase denoted by a different shade of blue.

Phase II: Verifying/improving the available data

As mentioned before, one of the most common issues when modelling UPF is the lack in, or low quality of, high-resolution data about hydrologically relevant features of the physical environment. Public involvement in an iterative process of data collection can identify and address some of these data gaps. The following activities were applied in Phase II to improve the quality (and, if needed, the quantity) of available data to better understand and model UPF by collecting as accurate and diverse data as possible from residents (Table 1). Most data were specifically related to a previous 'extreme' event. Additionally, we also collected some more data that were not directly related to any specific event (e.g. about the layout of the existing drainage system).

Table 1. Types of data that we attempted to collect in Phase II.

Data related to the previous extreme event	• Obtaining the depiction of runoff flow paths around a resident's immediate neighbourhood. For example, how water specifically moved around buildings and then entered the drainage system. • Exploring the possibility of runoff generation from open areas and its effect on the immediate surroundings. • Estimating water depths at specific locations by documenting high-water marks. • Obtaining basic, categorical data on water velocities.
General data	• Verifying/validating the boundaries of sub-catchments and whether these can interact during a flooding event: for example, whether the sub-catchment boundaries change beyond a certain rainfall intensity, correspondingly affecting water depths, and how such change affects the flow further downstream. • Describing in detail the spatial connectivity of impervious areas with their surroundings, especially in relation to the drainage system: for example, is the runoff generated from buildings' roofs directly piped to the street gutter, or is it allowed to flow over pervious surfaces after discharging out of the downspouts? • Increasing the level of detail about minor, local drainage systems (that are typically not represented in engineering maps), their functionality, and corresponding potential effects on runoff in case they do not perform properly. • Identifying the locations of small hydrologic features, such as fences, gutters, and landscaping berms, that might affect runoff patterns but are typically not captured through existing maps.

Phase II engagement with residents helped us pinpoint some clear flaws in our preliminary model. This led us to Phase III, where we reached out again to residents to further improve data quality and/or quantity.

Phase III: Improving and validating the model

Here, we improved the simulation capabilities of the hydrodynamic model, increasing its reliability through an iterative process. After an initial contact with residents in Phase II, the locally gathered data were compared to the results of the hydrodynamic model, in terms of maximum water depths and flooding extents, to identify some of its shortcomings and pinpoint those areas where improvement was still needed. Then, we again reached out to residents (red arrows, Figure 1) to collect further data using in-depth, face-to-face interviews. On such occasions, we shared results from the preliminary model (developed in Phase I of the research) – such as catchment boundary analyses, mapped flow paths, estimated inundation extents, etc. – even though we knew, and clearly indicated to residents that the output of the preliminary model might be inaccurate or lack some specific hydrological processes. However, sharing these preliminary results provided a foundation to deepen our engagement with residents, so that further meetings with them helped us expand and refine the data and information that were gathered in the initial exchange.

Phases II and III form an iterative loop: as model performance is improved in Phase III, further data needs, and more of the model's flaws, become apparent. For example, the performance may be inadequate at specific locations or it becomes evident that some parts of the catchment do not have sufficient data density for improving/validating the model, indicating that more or better data are required there. This takes us back to Phase II, reaching out to residents in an attempt at further improving data quality and/or quantity. This could mean surveying more people in general, talking to neighbours located in those specific parts of the catchment where the model needs the most improvement, or visiting people who were already contacted during the initial contact of Phase II to pose further questions.

Moreover, the iterative process allows for improving and validating the model at a higher spatial density (i.e. at more locations) within the subcatchments. This approach for densifying the sources of information can help address one of the main previously identified research gaps regarding UPF models: the fact that their parameters are usually calibrated only at a catchment's outlet in order to match observed outflow hydrographs, which does not ensure a correct representation of the physical events taking place within the basin.

Indeed, all three phases should be conceived as a bi-directional learning process since residents learn about UPF from the 'experts' while the 'experts' learn from residents about the neighbourhood's hydrological response, potential drainage issues, effects of previous events, etc. At this stage, we simultaneously address the bi-directional goal of the research by discussing aspects such as the potential causes of UPF (or currently increasing trends in rainfall intensities) and the outlook for sustainable, context-based interventions such as introducing Green Infrastructure [1] (GI) or Sustainable Drainage Systems[2] (SuDS) to decrease flooding risk.

In Phase III, we also try to deepen engagement (green arrows, Figure 1) by addressing other aspects of UPF, such as its broader socio-environmental context, the importance of sustainable development and/or solutions, and identifying potential ways to further involve residents in data collection. The research process will be followed by a demonstration in which the improved model will be used to develop different GI/SuDS intervention scenarios in terms of penetration or density, better illustrating how different levels of intervention would have helped (or not helped) in mitigating urban runoff under different rainfall scenarios – including the recent flood event. Results of this demonstrative study will be presented to the residents in a non-technical report, helping with future individual or organisational decision making (such as purchasing flood insurance), sharing findings with decision-makers to help re-think urban drainage, and improving knowledge of UPF, which can lead to further engagements for data collection. This type of interaction enhances communication with residents, improving their understanding of rainfall-runoff processes, flood impacts and risk, and potential interventions.

STUDY AREA DESCRIPTION AND ENGAGEMENT PROCESS

The city of Germantown (Shelby County, Tennessee, United States) was hit by an unprecedented storm on 7 June 2019 (Meier et al., 2019). The US National Weather Service (NWS) 'one-day observed precipitation' radar-corrected product indicated daily accumulations between 203 and 254 mm of rain in some sectors, but actual precipitation data from several privately owned rain gages reported event totals

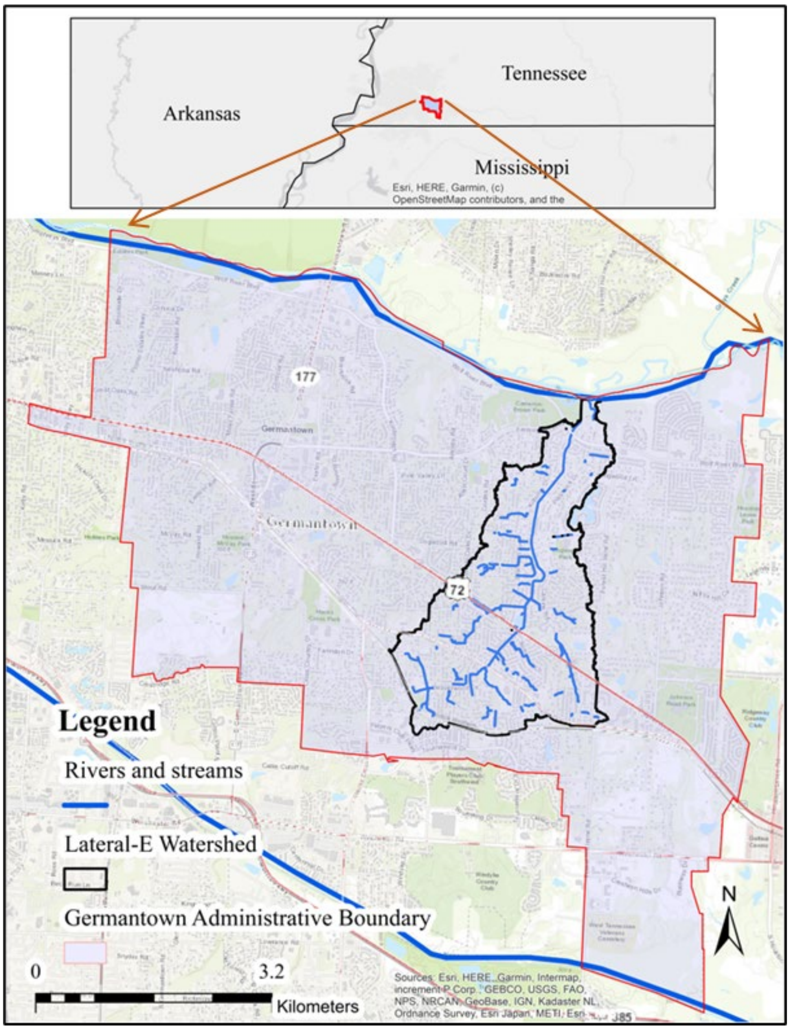
[1] The United States Environmental Protection Agency defines Green Infrastructure as a range of measures to store, infiltrate, or evapotranspire stormwater, or to mimic the natural water cycle by use of plant or soil systems, permeable pavements or other permeable surfaces or substrates, stormwater harvest and reuse, or landscaping, which can reduce flows to sewer systems or to surface waters.

[2] Sustainable drainage systems, as a part of larger green infrastructure strategies, are a group of water management techniques that seek to integrate modern drainage systems with natural water processes.

of up to almost 305 mm, with 4- to 6-hour maxima between 254 and 279 mm (https://www.wunderground.com/). The critical rainfall durations for this storm event were in the range from 2 to 6 hours. Specifically, for a 4-hour duration, an interpolation based on NOAA's Atlas 14 (Bonnin et al., 2006) estimates that, assuming stationarity, this part of the Mid-South receives 162 mm of precipitation or more on average only once every 1000 years; the 4-hour maximum for this event totalled 266 mm, 64% higher than the 4-hour, 1000-year event, reflecting an extreme recurrence interval (Meier et al., 2019).

The resulting flooding caused an estimated $7 million loss in structural damage to homes, with about 200 affected families experiencing issues ranging from major water damage to washed-out landscaping (Kennedy, 2019). The specific urban catchment that experienced the most severe impacts, that of 'Lateral-E' (previously called '17-Mile Branch'), was selected as the main study area so that the methods and analyses mentioned in the previous sections were performed for this part of the city (Figure 2). It is relevant to indicate here that Germantown was developed during the period in which the traditional paradigm for stormwater management (Dhakal and Chevalier, 2016) prevailed. Thus, its drainage system is designed to quickly remove runoff from streets using pipes, ditches, and mostly revetted urban creeks. Moreover, the city of Germantown is a rather affluent community, so the whole area is served by a stormwater drainage system that is usually well designed and maintained.

Figure 2. Location of Lateral-E catchment and the model domain area, Germantown, Tennessee.



The Covid-19 pandemic imposed restrictions on our access to residents; for example, we could have tried to engage directly with homeowner's organizations, but these were not conducting any type of meeting during the time frame of our research. Thus, we decided to initiate the engagement process by inviting a rather large proportion of the 'Lateral-E' catchment residents to participate in the research over the mail. To do so, 500 invitation letters were sent to people living within the catchment. The target residents were chosen based on the analyses performed in Phase I. Most people were selected because they lived close to vulnerable locations, as identified by our preliminary model. However, some of the letters were also mailed to a randomly selected sample of residents who lived within the catchment, though far from the potential risk areas. The letter contained a brief introduction to the research team and the research topic, and then explained our interest in documenting the 7 June 2019 event and the flooding it caused from the perspectives of residents. Specifically, we wrote the letter highlighting how community-based observations could help improve the hydrological models that civil engineers use for modelling rainfall events and designing stormwater drainage and runoff control systems.

The letter invited neighbours to complete a short online survey about their experiences during the June 2019 flood by answering simple questions about the event, mostly related to visual observations of aspects such as locations they saw flooded (streets, gardens, houses), approximate depths of water, whether the water was standing or moving, and the approximate speed of its movement, etc. Finally, the letter concluded with an open invitation for a face-to-face meeting, in case residents were interested in learning more about urban flooding issues and in further helping us. The survey was designed to address Phase II of the proposed research plan, while the in-depth interviews with residents correspond to Phases II and III.

METHODS

The research framework proposed in Section 2 was applied to gather information from the community using either online surveys or in-depth interviews (through face-to-face meetings) with interested residents, in a participatory modelling and mapping approach. This approach, also referred to as community-based mapping, is based on the idea that not only experts, but also residents from a neighbourhood, city, or region, may be involved in the process of geographic representation (Klonner et al., 2021; Saija and Pappalardo, 2022). Applying these methods sequentially, we iteratively collected information from the residents, allowing us to improve the performance of our preliminary model while simultaneously establishing a bi-directional learning process with the neighbours. This interactive approach enabled us to document spatial information of the urban catchment as well specific flood characteristics (Wolff et al., 2021) of the study area.

However, we had to resolve issues related to the fact that some time had elapsed between the flood event (June 2019) and the engagement process with residents (summer of 2021). This created challenges because as time goes by, memories can become vague (Lacy and Stark, 2013) and residents might lose interest in this kind of engagement. However, people who have experienced extreme flooding events will quite often hold a more accurate, detailed, and less-distorted memory of the event (Sotgiu and Galati, 2007). Our approach thus relied on residents' memories and applied iteration to minimise any external influence or memory distortions. This involved a field investigation with each resident in an iterative process to verify the information provided. We consider the site visits/meetings to be an essential aspect as the time elapsed between the flood event and our surveys and interviews was about 2 years.

Surveys

We sent out letters inviting 500 residents to fill an online survey about their specific experiences with the 7 June 2019 flooding event. These surveys served to establish an initial contact with residents, collect as unbiased information as possible about the focus area, and identify neighbours willing to further participate in the study. After establishing this initial contact with residents and collecting the first round of data, we invited interested responders to a short (~ 30 to 45 minutes) meeting, to deepen our mutual connection.

The online surveys requested information about (i) one or more locations that flooded 'sufficiently' during the June 2019 event, requesting time of observation, images of the event, estimation of water depth (e.g. based on high-water marks in the area), qualitative descriptions of runoff velocity, flooding extents, and perceived cause of flooding at each location; (ii) functionality of the stormwater drainage system during the event with respect to any drainage issues in the immediate surroundings; (iii) presence of small-scale features such as a garden walls, berms, raised footpaths, etc.; that could have affected the free flow of water during the event, blocking or diverting surface runoff from its intended path; (iv) surface runoff paths during the event (by requesting residents to draw a schematic map of their house and surrounding street(s), sidewalks, driveways, backyards, etc. and depict in as much detail as possible the observed flow paths); and (v) whether residents would be willing to be contacted for further discussion.

The online survey was published, and the responses collected, using ArcGIS Survey123, a multi-platform program for field-data collection. The surveys were created using this application, including map features that were linked to the base maps and imagery layers, allowing us to collect data for different spatial locations.

Out of the 480 residents that did get our invitation letter (20 letters were returned by the US Postal Service due to address changes or other reasons), 41 (or 8.5%) submitted a survey to our online ArcGIS Survey123 platform. The ex-post coding was performed to categorise the answers, collecting quantitative and qualitative data about the flooding event, but also to grasp the relationship between people and UPF. A total of 51 images depicting different aspects of the flood event were collected from the surveyed respondents (Figure 5), with the time of observation specified.

In-depth interviews through face-to-face meetings

At the beginning of the interviews with each resident, we briefly described the overall goal of our project and the type of data that we were looking for, highlighting the importance of their feedback in improving our modelling efforts. In order not to bias their responses, we first allowed residents to describe in their own words what had happened when they went through the 2019 flood event, what they observed, how they were impacted, what they thought caused the event, etc.

Many residents gave as many details as they could remember about the event including, for example, about the detailed extent of the flooding, the most impacted locations, the topographic conditions that caused the issue, flood damages around their or a neighbour’s house, relevant high-water marks, whether water was ponded or moving, etc. Some more informed residents also discussed broader issues such as the local or historical context of storm drainage infrastructure, previous events, etc. More details about the interviews can be found in the Appendix.

Towards the end of the interviews, we introduced hydrological concepts such as the importance of impervious areas and how their location and connectivity to the drainage system can impact hydrological response, and thus flooding. Finally, we gave residents a short introduction on different types of GI/SuDS solutions and how these can help in reducing runoff. To exemplify, we asked neighbours to think about the 2019 flood event and how its impacts could have been different if a given proportion of residents in the area had implemented a rain garden to collect runoff from their lot’s impervious areas instead of letting it directly flow into the street or drainage system, thus affecting the volume and timing of runoff. In closing, we mentioned that as a follow-up to our study, we would simulate the 2019 flood event under different scenarios of GI/SuDS introduction and share the results with them in an easy-to-understand, non-technical report.

Lastly, we also used these interviews to attempt to establish communication with other residents in the catchment. Therefore, we politely asked each interviewee to help us spread the survey and contact other neighbours that might have been interested in our research or in flooding issues in general. It should be noted that all the above-described activities collectively form an iterative process of identifying the model's shortcomings, collecting further data, and subsequently improving its performance.

Hydrological-hydraulic model development

EPA's SWMM (Storm Water Management Model) is one of the most commonly used numerical models to simulate urban drainage systems. However, SWMM is a one-dimensional model that lacks the features needed to simulate 2-D hydrological and hydraulic processes. On the basis of SWMM, Computational Hydraulics International (CHI) further developed a hydrological and dynamic model named PCSWMM (CHI.PCSWMM, 2020), which has the capability to couple 1-D flows, such as stormwater runoff in drainage pipes, with 2-D flows over land surfaces in order to simulate the rainfall-runoff process and evaluate the effectiveness of stormwater drainage designs. In this study, PCSWMM was used to run the UPF simulations to determine the extents of inundation, as well as point characteristics such as flow depths and mean velocities. PCSWMM is well-established and researched in the modelling literature and in engineering. Because it is a physically based model, it provides the opportunity to apply different types of observed data from various sources/locations (e.g. flow depths or velocities at specific points) and integrate them into the model's description of the UPF hydrological/hydraulic processes.

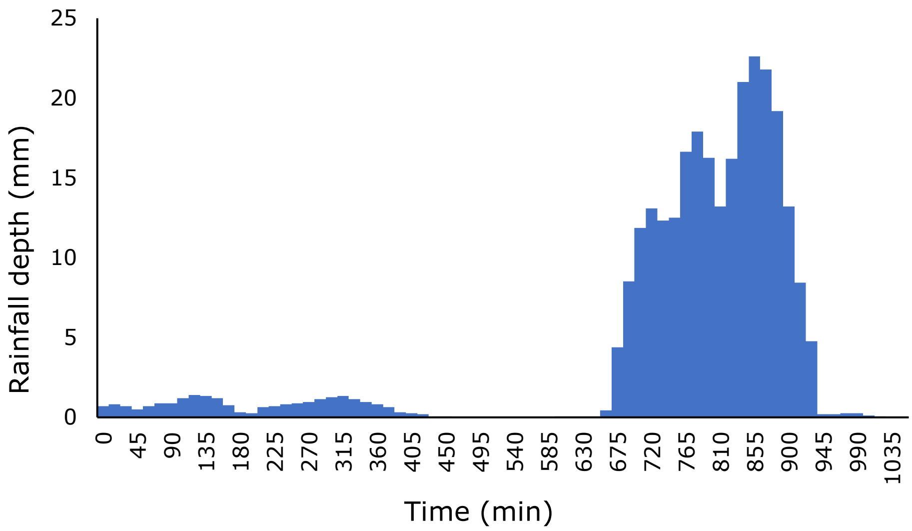
Model parameterisation

The municipality of Germantown provided data for the stormwater network within the catchment, which contains 648 manholes and 831 stormwater conduits conveying the runoff to the network of stream channels (Figure 2A). Regarding the calibration of the model, we should explain that because we did not have measured discharge data at the outlet (or any other location in the catchment), we did not calibrate the model's parameters in the traditional sense, but instead either used values that made physical sense (e.g. for the soil and infiltration parameters, knowing the soil types in this part of the world) or else considered default values based on the SWMM manual (for those secondary parameters to which the model was insensitive). However, a preliminary sensitivity analysis was carried out on some of the model parameters, including sub-catchment flow length, impervious percentage, depression storage for pervious area, depression storage for impervious area, Manning's roughness for pervious area, and Manning's roughness for impervious area. From these parameters, sub-catchment flow length and impervious area's depression storage were a little more sensitive compared to other parameters, but not enough to significantly affect the model's output. Not calibrating some of the parameters that are mostly related to the infiltration capacity of soils should not have a significant impact on the modelled catchment's response, given that local soils have low to very low infiltrability. Under these conditions, such a short-duration, extreme rainfall event is expected to result in a large runoff coefficient (i.e. most of the rainwater will be converted to runoff), so that errors in estimating infiltration losses have little effect on the model predictions. The specific details on model parameterisation can be found in Appendix.

Rainfall data

As there are no official NWS rain gauges in the sector that received the highest amounts of precipitation, the rainfall data were gathered from personal weather stations, as reported to The Weather Underground website (www.wunderground.com). One such gauge, approximately located at the centre of the Germantown Lateral-E catchment, was analysed in detail by extracting the rainfall hyetograph at 15 min intervals (Figure 3), which was then assigned to all subcatchments. It should be noted that both the rainfall depth total as well as its time distribution over the catchment were highly uniform, as shown by the U.S. National Weather Service 1-day observed precipitation product for 7 June 2019 and by the analysis of Meier et al. (2019) of five Weather Underground rain gauges, of which four were located inside and one immediately beside the catchment.

Figure 3. Rainfall hyetograph for the 7 June 2019 event in the Lateral-E catchment, obtained from a privately-owned rain gauge reporting to The Weather Underground website. Each bar shows the rainfall depth (in mm) per 15-minute period.



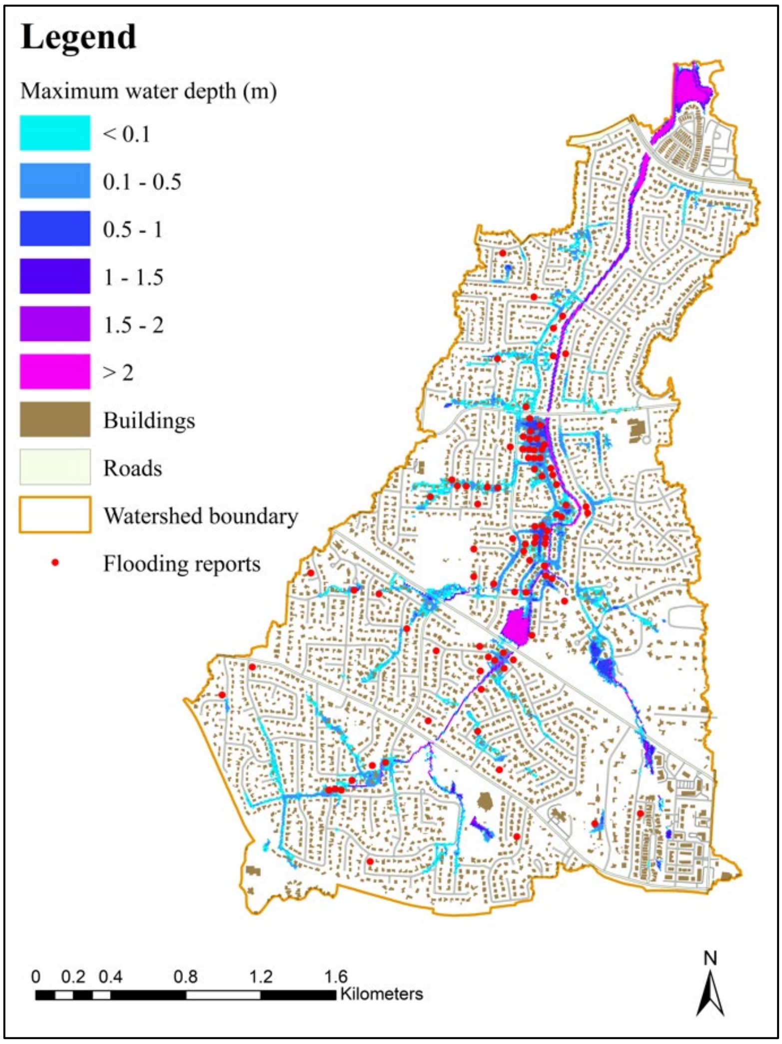
Results

Phase I

Applying only existing, physical data like LIDAR, DEM data, rainfall event data, stormwater infrastructure data, and official land-use maps, the inundation extents for the 7 June 2019 flood event were simulated for the Lateral-E catchment, using the 1D-2D hydraulic model PCSWMM. Figure 4 shows the resulting inundation extents map, depicting the spatial distribution of modelled water depths; the map also shows those locations that reported flooding, as reported to City of Germantown officials by affected neighbours.

There are no stream gauging stations within Lateral-E's catchment. Due to this lack of observed time series of water levels and discharges for the actual event that we are attempting to simulate, no calibration process was performed at this stage. To better identify and characterise UPF risk, the preliminary model results were compared with the flooding reports collected by the city, which show 96 flooded locations within the Lateral-E catchment. However, these only describe the flooding conditions in a qualitative fashion, such as 'interior and exterior damage', 'flooded yard /home/ street', etc.; without providing any quantitative information about water depths, velocities, or flooding extents. Most locations reporting flooding are captured by the preliminary model. Still, comparing the preliminary modelling results with the flood reports does indicate that some locations that actually flooded during the event were not captured by the model's results. There are many reasons why such issues could happen; for example, there might have been cases of clogged drainage systems or obstacles such as walls, construction debris, etc; that are not captured by the DEM or the existing physical data and maps. The model's findings from this initial phase were used to initiate a dialogue with the community, engaging residents in our research with the aim of collecting further data and information, and performing participatory mapping activities.

Figure 4. Flooding extent for the 7 June 2019 rainfall event, as determined by the preliminary model.



Phase II

From the 41 residents who completed the online survey, 40 (97%) stated that the flooding they observed had happened at a location "immediately across or in the vicinity of my home" (Table 2). This reflects that residents' personal flooding experiences and flooding memory strongly influenced their willingness to participate in the survey. Concerning flooding depths, 73% of residents could remember a precise water depth, while 27% could only estimate flow depth according to four predefined, broad depth categories. Even though most respondents were describing flooding very close to their homes, only about 40% of them attempted to answer the question about flooding extent by drawing polygons depicting inundated areas (Figure 6). This suggests that some might have had issues inputting this information into the platform. It should also be noted that many people answering this question about areal extent of flooding just drew very simplified geometric figures, strongly suggesting that these results are not very accurate.

Even though the question regarding estimation of water velocity might not be of much value to improve the hydrodynamic model's performance, it could be useful in planning practice, to mitigate local risk. For example, such information could help identify locations that could use some type of landscaping improvements, locally increasing roughness to decrease overland flow velocities. About 64% of respondents answered that water was moving fast, among the four categories of 'very slowly- basically standing water', 'slowly', 'fast', and 'very fast'.

Table 2. Survey results.

Location of the observation (n = 41)		*Water depth (n = 41)*	
This happened at, or immediately across my home	54.5%	I know the exact depth of water based on marks left by the flooding; for example, a car or a mailbox was in the water up to a certain depth	72.7%
This happened in the vicinity of my home	42.5%	Approximate estimation of maximum depth of water according to 4 relative categories	27.3%
I don't live close to this location	3.0%		
*How did the flooding affect the immediate surrounding area? **		*Likely cause of flooding **	
It only caused street flooding	43.9%	Extreme rainfall	60.6%
It caused water accumulation on sidewalks, too	43.9%	Inadequate capacity of the drainage system	51.5%
		Relief or lay of the land (topography)	45.5%
		Maintenance issues with drainage system	39.4%
It caused further issues, as described below	63.4%	Absence of a stormwater drainage system	3.0%

Estimation of water velocity at the specified location (n = 41)			
Very slow – Basically, standing water	Slow	Fast	Very fast
9.1%	15.2%	63.6%	12.1%

Invitation for further help (n = 34)	
Yes, you can contact me if you have questions	51.2%
Yes, I am interested in having a meeting	31.7%

Note: * Residents were asked to choose multiple responses.

Regarding the cause of flooding, 61% of respondents referred to extreme rainfall. Almost half the respondents placed the blame on inadequate capacity of the drainage system, while 46% and 39% of the surveys indicate that topography and maintenance issues with the drainage system, respectively, caused the flooding. Moreover, only 3% identified "the absence of a stormwater drainage system" as a cause for the flooding, even though the totality of the Lateral-E catchment is served by what could be considered to be a well-designed and well-maintained stormwater drainage system (if adhering to the traditional urban stormwater management paradigm). These results suggest that: (i) the vast majority of residents do know that their street has a stormwater drainage sewer, (ii) slightly more than half opine that its design capacity is adequate, and (iii) most neighbours think that the rainfall event was extreme.

Figure 5. Typical images collected in the online surveys that show different information about the flood event, such as watermarks in various locations and impacts of the flood on the area.

Regarding the functionality of the drainage system, 23 locations with issues were identified according to the responses to the online survey (Figure 6a). When asked to describe the 'effects of drainage issues', 44% of respondents stated that these resulted in street and sidewalk flooding, while 63% said that they caused further issues. The problems that were most commonly pointed out were water flooding backyards, houses, or parked cars. Unfortunately, we received no survey answers about our request to map the locations of any small hydrologic features that could block or divert surface runoff from its intended path. This shows that either this question needed further context for residents to be able to answer it, or else they never observed such phenomenon during the flood (which occurred at night) or during any other rainfall event. In case it was the former, we tried to address it again in Phase III, when we had an opportunity to explain some hydraulic and hydrologic processes in more detail to residents. However, it should be noted that in their attempts at explaining their answer to this question, some respondents provided valuable explanation about other potential issues. Particularly, there were detailed descriptions of clogged drainages and culverts due to drifting debris from upstream, claims of lack of maintenance of curbs and gutters, collapse of a retaining wall next to a ditch, etc.

In this phase, we evaluated the model's performance by comparing its predictions with water depths collected from residents' surveys (either identified by respondents or extracted from the pictures they sent). It quickly became apparent that even though it performed adequately in some sectors, typically located upstream of the ditch network, closer to the headwaters, its results were quite flawed at some specific locations along Lateral-E and some of its tributary drainage sewers. It was evident that the flooding extents and maximum water depths depicted by the model at such locations were inaccurate (Figure 7). This led us to Phase III, where we reached out to residents with the intention to improve data quality and/or quantity at, and around, these specific locations. To effect this higher level of engagement, two types of invitations were sent to interested residents based on their answers to the request for "further help" at the end of the survey. In this request, we asked them to allow us to either ask more questions (over the phone or by e-mail) or have a short face-to-face meeting with them.

Figure 6. Participatory community mapping results; (a) Details of flooding locations, flooding extents, and drainage issues; (b) Samples of collected flow-path maps.

(a) (b)

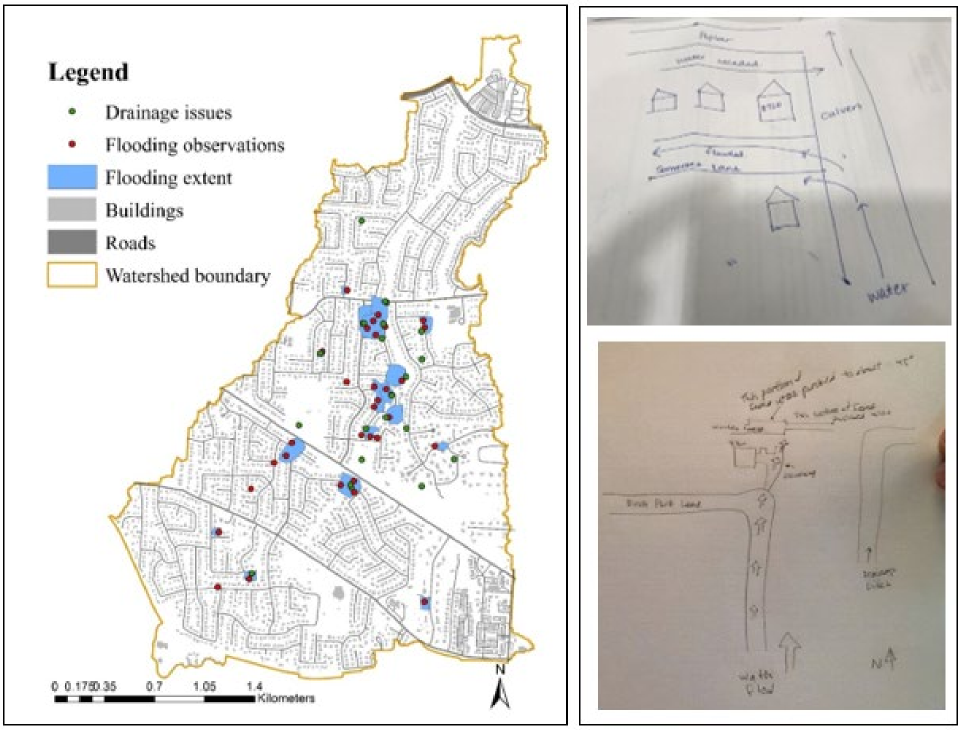
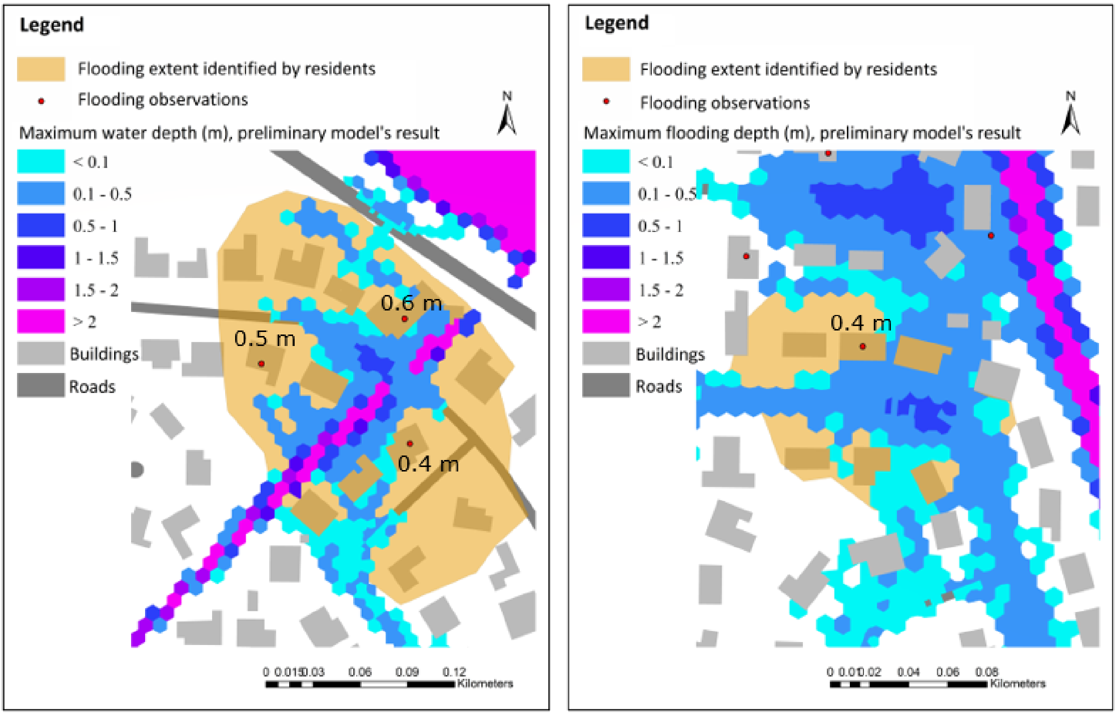


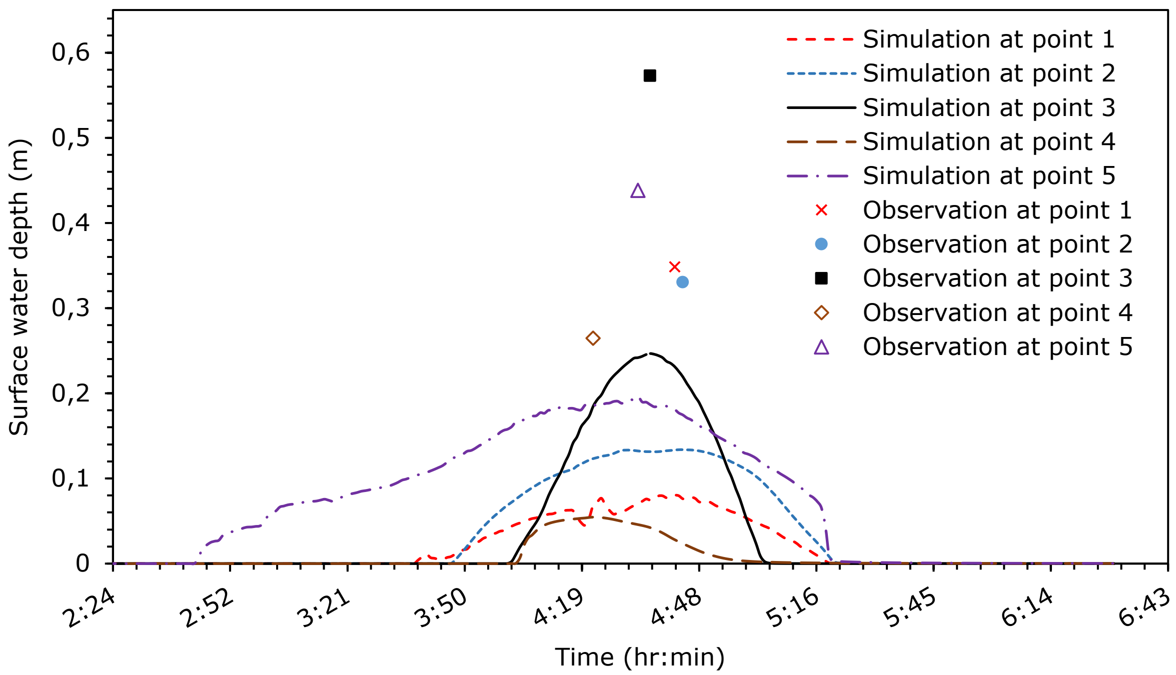
Figure 7. Comparing the preliminary model results to flooding observations by residents at two different locations close to the mainstem, where the model substantially underestimated flooding extents and depths.



Phase III

As mismatches between the model's results and reported flooding extents and depths became apparent at some locations closer to channels during Phase II, we reached out to interested residents and collected more detailed data through in-depth interviews in order to improve our representation of the event. Either from photographs, from memory, or from persisting high-water marks since the flood occurred, the neighbours helped us identify a series of locations with well-known maximum water depths. These were surveyed with an auto-level, referring their elevations to known features, such as sewer manholes. Comparing depths at these 'ground-truthed' locations with the model's preliminary simulations (Figure 8) made it clear that there could be large differences between our simulated results and resident-observed depths. This was particularly true in some sectors located close to the main channels, in which the flooding was more 'fluvial' even though still of the 'flash flood' type. However, the model seems to perform quite well in reproducing UPF in locations far from the main tributary of Lateral-E where the flooding was 'true UPF' (unaffected by channel hydraulics, over what we are calling 'upland areas'). In this manner, in an iterative process of data collection while conversing with the residents, we attempted to improve the details of the model at as many of these locations as possible.

Figure 8. Evaluation of stage hydrographs from our preliminary model (curves depicting how flow depth changed with time at specific locations, as simulated by the model) versus actual maximum water depths at the same locations, as reported by residents for five locations close to the main channel, where the model substantially underestimated flow depths.



We did participatory mapping with residents to obtain a range of details in order to improve the representation for the local subcatchments. For example, we explored the runoff flow paths around their neighbourhood to identify and validate the previously identified drainage outlets in each subcatchment. We verified and validated the boundaries of the subcatchments, as delineated in Phase I. We investigated the spatial connectivity of impervious areas to the drainage system, checking whether the roof downspouts are directly connected to the drainage system or not (with the typical black, corrugated plastic pipe). We also walked around each resident's house and yard attempting to identify any features around their property that could block the water flow but were not captured in our preliminary model.

After collecting these hydraulic/hydrological data at the smaller scale, we incorporated them into the model. For example, in the case of the exact location of roof downspouts and their possible direct connection to street gutters, we refined the model resolution for each subcatchment, including details at the building or driveway scale. To evaluate the improvement achieved by applying the participatory modelling approach and locally validate the model at a higher spatial resolution, results obtained from the improved model were then compared with those from the preliminary version, as well as with the resident-obtained data.

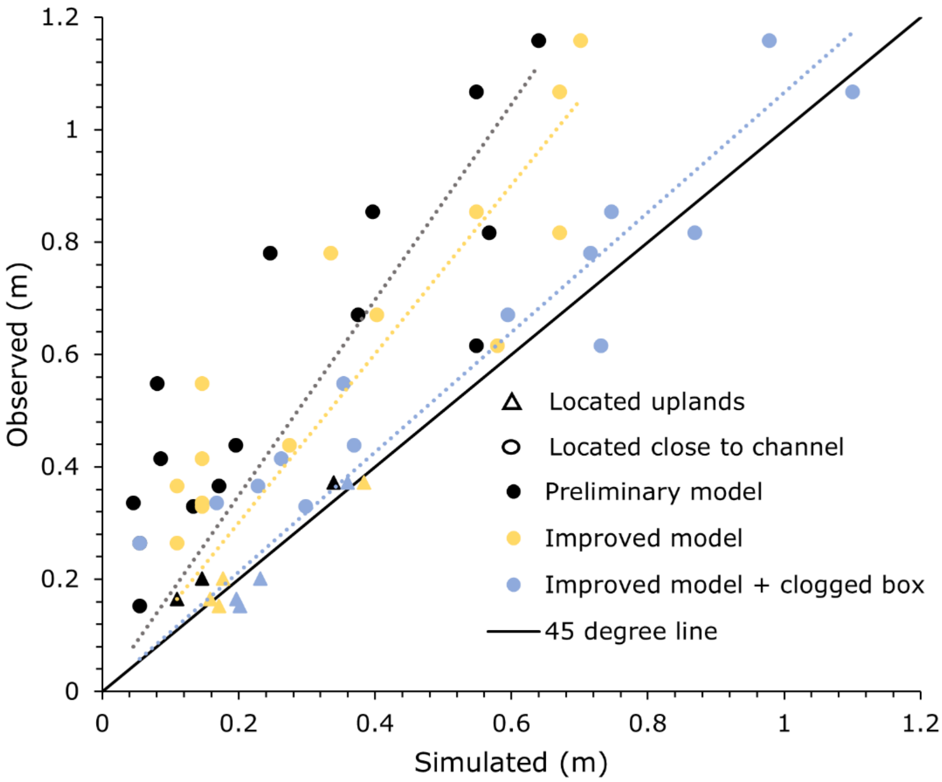
To evaluate the validity of model results, three statistical measures were used: the correlation coefficient (R), the root mean square error ($RMSE$), and the mean absolute error (MAE). Even though the simulated depths and flooding extents generated by the improved model are closer to the actual observations, the enhancement does not seem that significant at first sight. One reason for this might be that we did not interact with a sufficiently large number of residents, so that many areas within the catchment could still be missing data needed to improve their representation; for example, some smaller-scale features could be absent or misrepresented at more locations than those included in the improved model. In this respect, it is important to note that there is a spatial bias in our sample of residents: many of the people who decided to enrol in the study, either by answering the survey or meeting with us, do live near the mainstem of Lateral-E – the area that suffered the worst flooding impacts. Increasing the total number of respondents and, perhaps more importantly, attempting to specifically recruit residents uniformly across the catchment would result in a more accurate model overall. A better representation of the catchment and the actual hydrological-hydraulic processes occurring in it would allow us to better simulate flooding extents and water depths not only for the flood that occurred, but also for any other storm event. These modelling results could then be utilised (by decision makers) to inform a range of potential decisions to improve drainage conditions in the area.

Moreover, given the catchment's size and notwithstanding our findings of a spatially uniform rainfall event, it might be that more rain gauges would be needed to represent the actual spatial and temporal variability of rainfall intensity, so as to not underestimate the local response at some locations. An enhanced network of rain gauges and quantitative community-based observations (total rainfall, timing, duration, and intensity), alongside traditional sources of hydro-information, could help in capturing the spatial and temporal variability of rainfall events, especially in the case of those intense, short events that typically cause UPF.

However, we posit that there is another, more important factor explaining why the model underestimates flow depths at many of our studied locations, when they are close to the main channel or its main tributary. During our face-to-face meetings, residents repetitively described a third potential explanation for the model underperforming at such locations: the physical conditions of the open channels ('ditches') in the catchment. Many neighbours pointed out specific channel locations at which bridge-size culverts (either single or multiple box) had clogged, even mentioning the potential culprits (e.g. a large tree, a garbage dumpster, or railroad ties that drifted from a garden located upstream). This type of effect did probably occur immediately upstream of two specific culverts, where our simulated depths and flooding extents were much smaller than those observed and reported by the neighbours. In one of these cases, it was impossible to model the effects of a potential obstruction, as we did not have any information (it was a single box culvert and the flood occurred at night). In the second case, upstream of a triple box culvert (depicted in Figure 3A), we attempted to improve the model by exploring the hydraulic effects that would have occurred if one of the three boxes had indeed clogged during the 7 June 2019 flood, as was suggested by some residents.

Figure 9 shows the comparison of results for the preliminary model, improved model, and improved model in the case of a clogged box at the 18 locations where maximum flooding depth was precisely measured in the field using information provided by the residents. Overall, the model seems to be quite capable of representing the upland sectors (with depths shown in triangular markers), as all those locations at which there are larger discrepancies between the model and the flooding reports are along the mainstem of Lateral-E. Together, these facts suggest that our catchment-wide estimates of roughness and infiltration behaviour are correct, so the model's biases are mostly due to an incorrect representation of fluvial hydraulic processes at locations along channels. Furthermore, because the model is capable of adequately representing the hydrological processes in upland areas, the fact that there are issues around channels must be due to some misrepresentation of hydraulic features/details, e.g. incorrect channel shapes or capacities at road crossings. Therefore, any attempt at calibrating hydrologic parameters without accounting for those hydraulic issues would result in a misrepresentation of catchment characteristics.

Figure 9. Scatter map between observed and simulated water depths.



The results suggest that the possibility of a clogged culvert is a valid hypothesis, as the simulated results near the main channel are much closer to the actual, observed maximum depths and flooding extents under this scenario (Table 3). Significantly, the corrected model predicts with a higher level of accuracy as the locations get closer to the culvert. The improved model considering one clogged box performs better according to all three statistical measures, with a correlation coefficient as high as 0.93. Even though these results are contingent upon an assumption about clogging based on reports from multiple residents, they highlight how our proposed approach of incorporating local knowledge can significantly impact or even completely alter the characterisation of catchment response and flooding.

Table 3. Evaluation of the preliminary and the two improved models.

Indices	R	$RMSE$	MAE
Preliminary model	0.84	0.32	0.27
Improved model	0.87	0.26	0.21
Improved model + clogged box	0.93	0.12	0.16

DISCUSSION

This research proposes a citizen science approach to understanding UPF's complexity and better characterising and modelling it. The proposed approach expands traditional citizen science concepts to improve current urban flood modelling and data collection techniques. It provides an avenue to apply a more comprehensive and integrated participatory modelling framework towards a better understanding of UPF risks and vulnerabilities, by exploring ways in which residents can be involved in urban flood risk assessments, data collection, and model development for their neighbourhoods.

Addressing data gaps and improving hydraulic/hydrological model

In practice, as previously discussed, urban flood models are continuously developed and applied (e.g. for use in 'catchment master plans'). But in too many cases, such models are probably not accurately capturing what occurs over the slopes and streets inside an urban catchment. In the best case, a calibrated model might accurately depict the flow discharges (and depths) at the outlet or some other specific point along the mainstem or a tributary. When dealing with UPF though, we need to know what is going on everywhere in the basin (for example, potential flow depths); calibrating a model so that its output matches previously measured discharges at a single location (the outlet) is thus inadequate for understanding UPF and the impacts of potential solutions. In our study, we obtained information that is neither typically available nor used in engineering models, which helped improve the modelling results. The model performed adequately over 'upland areas', i.e. it got the hydrology right. This aspect is encouraging considering that we only had very limited 'resident-based' evidence for ground-truthing flow depths in headwater or 'upland' sectors. Basically, our sample was 'biased' towards residents living close to the main channel because people were more willing to talk to us if they had been affected more severely by the flood, which was the case at locations close to the main channels and not in the upland areas. This also explains why the 'improved' model without changing the box culvert did not yield that much improvement at first sight. Because most of the fine-scale hydrological tuning that was incorporated into the model was at locations close to the main channel, that were truly impacted by the hydraulic (backwater) effects of culvert blocking, it should be expected that changing the surface hydrology would not affect results too much at such downstream locations.

Regarding the challenges of the quality and reliability of citizen science data that were discussed in the introduction section, it should be noted that all our depth data were gathered either from clear photographs taken the day after the event or from resident-identified extant high-water marks (for example, on garage doors), allowing us to accurately ascertain the locations. Using an auto level to tie the elevations of the targeted places to the elevations of surrounding manholes gives these data an accuracy in the order of +/-2 cm. Much of the current criticism of citizen science lies in the fact that residents who lack scientific training are provided equipment and asked to perform data collection, and thus can introduce measurement errors. In our case however, the information gleaned from the residents related only to the existence of high-water marks (depths) and physical features with hydrological relevance; after they showed us the evidence, we performed the measurements ourselves. In light of the research gaps in UPF research and the objectives of our study, we trust that the type of information collected from the residents does add a new layer of knowledge about different characteristics of the catchment and the event, improving our representation of UPF.

Engaging residents in the research and a bi-directional way of mutual learning

This study provided a context for exchanging knowledge between residents and experts regarding UPF modelling and characterisation. The iterative nature of the research approach made it possible to share our findings about UPF, coupling this with the acquisition of ground-truthed data from residents. Moreover, the residents' awareness and interest about their local drainage system and the hydraulic and hydrological conditions of their surrounding environment, that was clearly displayed during the meetings, proved to be an important and valuable feedback in improving our own understanding and characterisation of local UPF issues.

In terms of enhancing resilience to flooding at the neighbourhood scale, we recognize that simply conducting in-depth interviews with a few interested residents will not have a significant effect across the community. However, the interaction helped them understand that there are several issues that they had not been aware of. For example, in the US, it is a common mindset among residents that if you are not in a federally delineated floodplain, according to FEMA Flood Insurance Rate Maps (FIRMs), it means that you should not have any flooding issues. All the residents contacted in our study are well educated and live outside of 100-year floodplain (i.e. the zone that would have a 1% annual chance of flooding due to fluvial events), and most of them are also outside of the 500-year special zone. Only after interacting with us did they realize that floodplain delineation in FEMA's FIRMs accounts solely for fluvial flooding, whereas any location could be hit by pluvial flooding. We opine that through this knowledge, and the visual representations of their surrounding environment that were used to introduce and explain UPF, neighbours will be better capable of understanding it and be prepared for its risks. We also believe that discussing technical concepts with residents can contribute to resilience by clarifying misconceptions and assumptions about urban flooding risk. Even though Šakić Trogrlić et al. (2019) argue that these types of contributions might be limited in terms of the benefits they provide, or these could be only considered to be potential benefits (Walker et al., 2021), we nevertheless believe that they contribute to the resilience of communities affected by flooding in that they empower people to use their local knowledge and take action (Stepenuc and Green, 2015). Therefore, we posit that in this pilot study, at the level of individual residents and maybe some of their neighbours (but not at the community scale), we have improved their knowledge about flooding. By discussing flood insurance and explaining that it should not be expensive outside of FEMAs 100-yr floodplain but will still cover against UPF-caused losses, we have enhanced their preparedness and recovery capability. In this context, we argue that our study helped empower individuals by increasing their human capital, thereby allowing them to make better-informed decisions. Moreover, by situating this research in relation to other recent projects that have involved communities in a similar way (Conrad and Hilchey, 2011; Shirk et al., 2012; Walker et al., 2021), we can justify that bi-directional learning facilitates contributions to resilience in the long run by providing knowledge improvement (Wolff et al., 2021) and awareness as mechanisms for communicating risk, preparedness, and recovery capability (Cheung and Feldman, 2019).

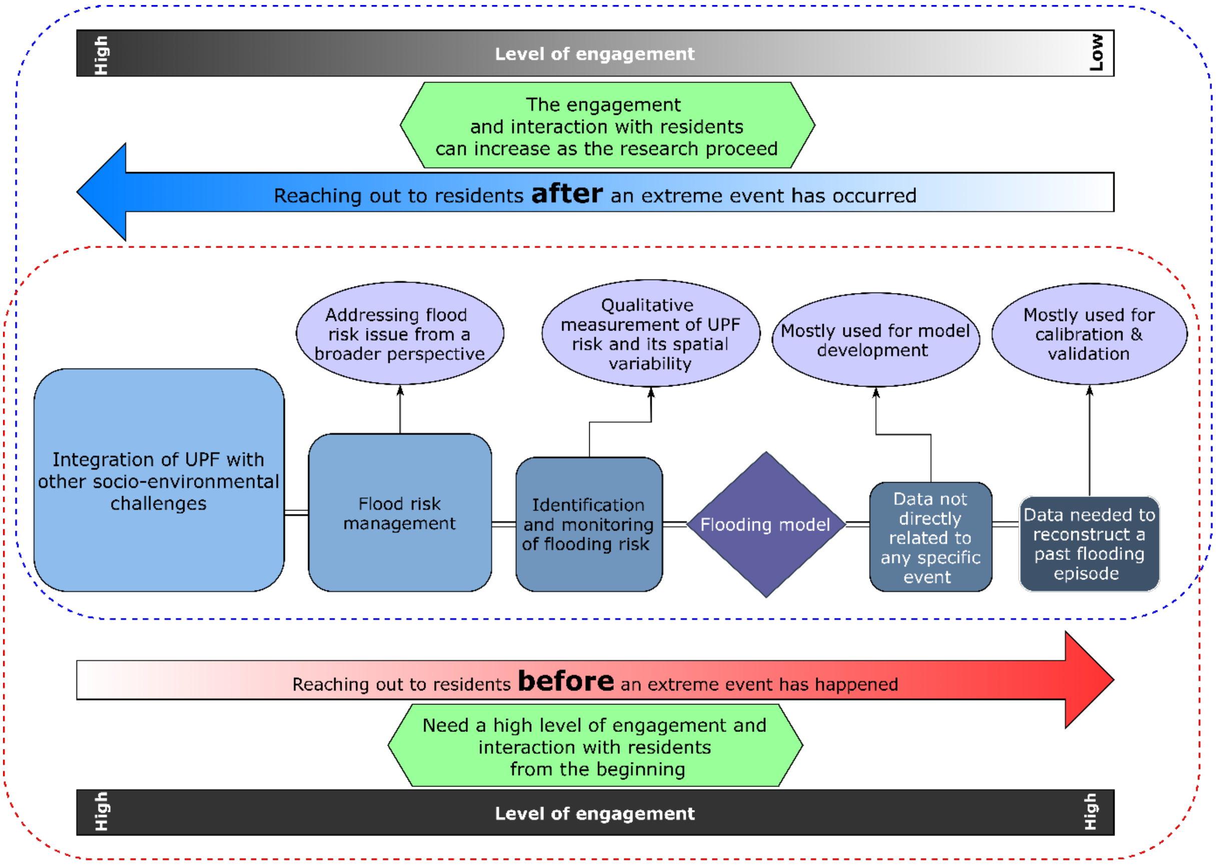
All in all, the residents involved in this project's various phases have an enhanced understanding of flooding processes, which they can integrate into any future decision-making process regarding flood risk. Indeed, our approach provides pathways to contribute to UPF resilience over the long term. This also highlights how the second research objective, which focuses on involving locals and using citizen science in a bi-directional manner is being addressed. Regardless of the limitations mentioned above, the level of improvement achieved with the limited resources we afforded in this study clearly shows the potential for further model improvement with subsequent, larger-scale data-gathering campaigns involving residents. Given more resources and time (and a non-pandemic setting), we could have involved community organisations and upscaled our preliminary and pilot results to a scale closer to the community level.

Feasibility of employing the current methodology in a different context

The effective application of citizen science approaches to address the current issues in UPF research is a challenging task. In this study, we tried to approach some of the current challenges with a systematic, multi-phase community-engagement process that collected detailed residents' observations of UPF variables of interest. Even though the results were case specific, the methodology is transferable to other localities and could be effectively applied in various contexts. However, each case will have its own unique characteristics that need to be considered.

One specific issue that should be relevant when attempting to apply our proposed approach is the timing of the study, in the sense that engagement with the community can occur either after an extreme event has already occurred locally, or else in the case in which it has not occurred (yet). This factor can significantly alter the way that research should proceed, as well as the initial level of interest from residents. As proposed in Figure 10, when reaching out to residents after an extreme event, they might be more willing to participate in the research in general, and data collection in particular, when the impacts and fresh memories of a recent flood are still lingering. This would provide an opportunity to start with a lower level of engagement (as performed in this study) and increase it as the research process progresses. In our case, the past event provides a focal point to initiate the conversation with residents.

Figure 10. Engagement process with the community based on the timing of the study, i.e. whether reaching out to residents before (red) or after (blue) an extreme event has happened in the neighbourhood.



On the other hand, when the research involves a locality where no large flood has occurred yet (according to local memory), we propose that it becomes much more important to establish a high level of engagement from the beginning and maintain it through the process. To motivate people, engagement processes should highlight the importance of UPF, bringing it to their attention. One way to do so might be mentioning UPF events that have happened recently at relatively close locations.

Citizen participation and motivation are primary requirements for citizen science programs to succeed (Rotman et al., 2012). The most significant challenge we faced when applying our proposed methodology was to access a sufficiently large number of residents, and subsequently to be able to engage them in the different phases of the data-collection process. These are vital aspects when attempting to effect meaningful impacts on rainfall-runoff modelling over larger catchments. One option to increase the proportion (and the willingness) of residents that participate could be to engage local organisations and work with community leaders. This could ensure a better acceptance of the project, subsequently allowing researchers to reach out to larger numbers of residents (Sy et al., 2019).

CONCLUSIONS

This research's findings make it clear that a deeper level of resident involvement can provide valuable inputs via citizen science-style data collection activities for a range of pertinent topics related to catchment characterisation and rainfall-runoff modelling. Even though community-based activities are less complicated, significantly cheaper, and less demanding than some of their traditional counterparts (e.g. sensors), our results highlight how effective and valuable they can be in characterising and modelling UPF. The examples presented herein emphasise the importance of obtaining adequate spatial and temporal information at the subcatchment scale.

Three key conclusions can be drawn from this work:

- Our modelling results illustrate how quantitative and qualitative community-based observations are required, alongside traditional sources of hydro-information, to fill spatial and temporal data gaps and characterise local, within-the-catchment response more accurately than could be done with traditional data alone.
- Community-based observations can add spatial detail and help in ground-truthing existing traditional sources of catchment data.
- The framework we are proposing shows how community-based practices provide a bi-directional learning context between experts and residents, which should result in enhanced contribution to UPF resilience, neighbour by neighbour.

It is acknowledged that the results presented here are location- and event-specific. However, the study provides an insight into the added value of resident participation in integrated UPF modelling processes, together with its potentialities. The outcomes of the engagement process and participatory mapping can evolve and improve over time given that citizen science is flourishing in line with new technological advances. Despite the natural limits created by participation levels, this will allow for easier and more efficient ways to collect and process data.

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APPENDIX

More details on the structure of in-depth interviews

We shared results from our preliminary model, explaining that it had been developed using the 'traditional engineering approach', i.e. based only on physical information such as LIDAR data, types of surfaces (impervious or pervious), characteristics of the primary drainage system, and data about the actual rainfall event. Then, we proceeded to explain our hypothesis in more detail: that rainfall-runoff models typically used for design and management of storm water drainage systems can be improved by obtaining local information from community members.

Preliminary model results were shown at two spatial scales: first, depicting maximum flooding extents over the whole catchment, approximately locating the resident's house, and then zooming in to the level of the immediate neighbourhood (with the resident's house clearly centred, surrounded by the neighbouring properties), showing more detailed results this time. As the interviewees visualized the maximum flooding extents, as well as the color-coded depths, they were quick to note errors and suggest corrections. In this way, we were immediately able to identify areas in which our preliminary model was evidently inaccurate. We then attempted to capture maximum flooding extents around the immediate neighbourhood, for example, which specific houses or parts of a street were (or were not) flooded, with approximate water depths. After obtaining this type of information, the conversation was focused towards the possibility of procuring accurate high-water marks. We directly asked the residents whether they could remember specific locations where such levels were clearly recorded, and if they could not, we suggested that they could be obtained from pictures they may have taken during/after the flood. In such cases, we attempted to extract flood elevations using reference objects such as existing trees, posts, fences, etc. Once we identified adequate high-water marks, either remaining since the event, or from direct memory or the use of pictures, we proceeded to use a surveying auto-level to relate their elevations to those of neighbouring manholes or grate inlets (which are known).

In the next step of the interview/meeting, we asked residents to schematically depict the drainage system around their house, mapping any smaller drainage inlets that might not be captured through currently available data. This exercise was conducted with the aim of gaging whether people have any kind of sense of their local stormwater infrastructure and how it works. We then gave them a map that closely reflected the physical environment around their house and asked them to draw how water flows around their house and into the closest drainage, when it rains. Next, we visited their front- and backyard, walking together around the house, and checking for flow paths, how water flows out of their property, and the presence of any feature blocking or redirecting water. We also asked them about the locations of their roof downspouts, and whether these are directly connected to any impervious area (driveway, street gutter) or not.

Model development and parameterisation

The 7.49 km^2 catchment was subdivided into 488 subcatchments using the catchment delineation tool from PCSWMM with the application of a 1-ft resolution LiDAR map as the Digital Elevation Model (DEM). The Manning's roughness coefficients were adopted from SWMM manuals (Rossman and Huber, 2016); impervious areas (N Imperv = 0.03); pervious areas (N Perv = 0.4); and conduits (N Cond = 0.014). Depression storage for impervious and pervious areas was considered to be zero (Dstor Imperv = Dstor Perv = 0), because we are assuming that surface depression storage will be explicitly represented by the topography in the 2D model, given the high resolution of the DEM and 2D cells. The parameterisation of the subcatchment area, width (length), slope, and the fraction of impervious cover was performed using subcatchments layers and land-use layers through catchment conceptualisation.

The two-dimensional mesh representing land surfaces was generated with the hexagonal style and a spatial resolution of 15-ft with the Manning's n-value set to 0.033. In addition, a 5-ft resolution directional mesh with a roughness of 0.014 was set to the roads. Overall, 596,678 nodes were generated. Afterwards, the one-dimensional pipe system was connected with the two-dimensional model through bottom orifices, thus forming the coupled model. The bottom orifices technique is a setup used in dual-drainage modelling (1D and 2D), where two-dimensional surface runoff flows into 1D nodes of the pipe drainage network through conceptual orifice connections.

Figure 1A. Simplified development process of a typical urban flood model in PCSWMM.

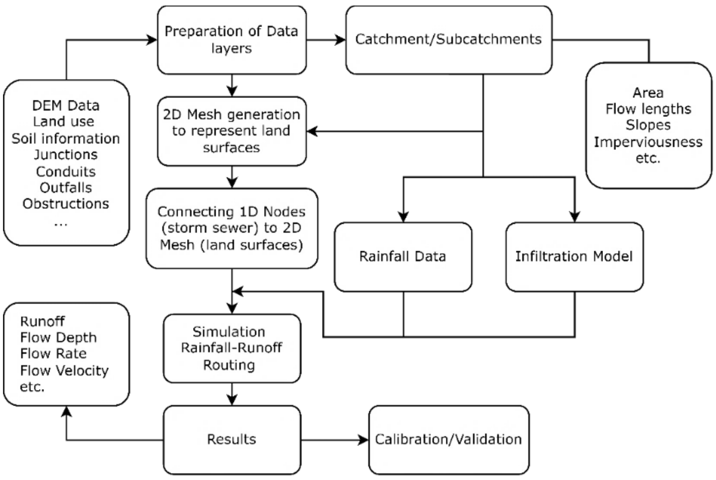
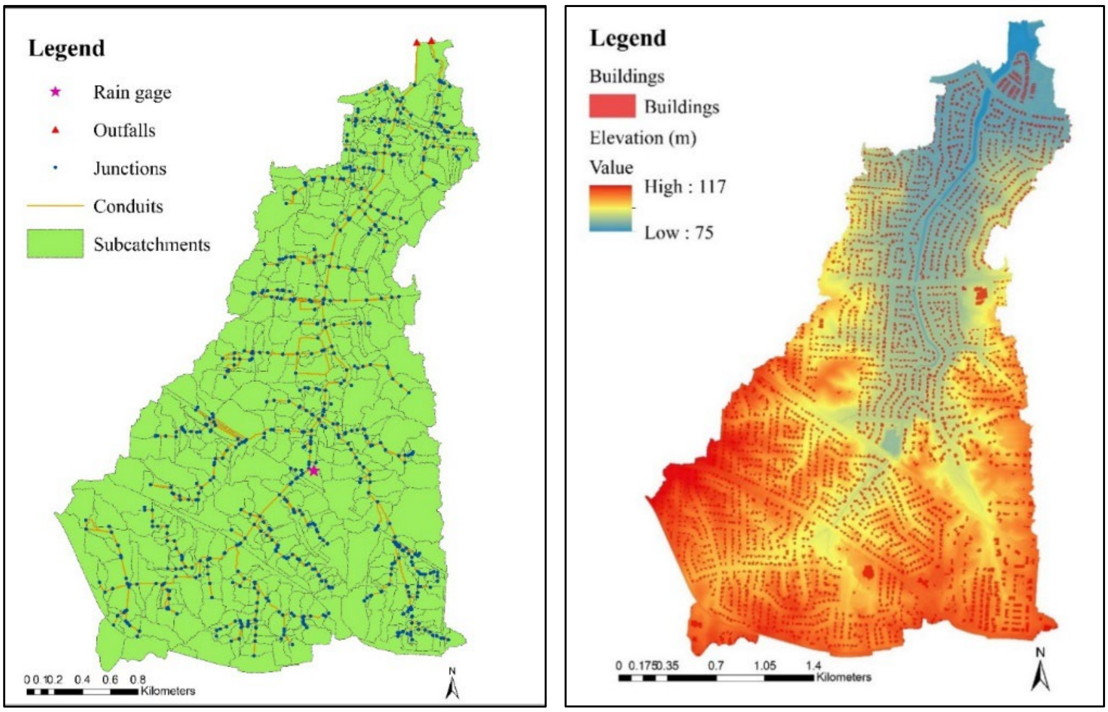


Figure 2A. Catchment characteristics: (a) Catchment boundary, subcatchments, and drainage system; (b) Terrain and buildings.

(a) (b)



Clogged culvert hypothesis

Figure 3A. Upstream (left) and downstream (right) view of a multiple-box culvert located over Lateral-E inside our study catchment, for which the residents suspect clogging occurred during the 7 June event.

Note: These pictures were taken on a different date and thus do not represent the culvert's actual condition during or immediately after the studied flood.